SECOND CHANCE: LIFE WITHOUT STUDENT DEBT*

Marco Di Maggio[†], Ankit Kalda[‡], Vincent W. Yao[§] April 27, 2019

Abstract

Rising student debt is considered one of the creeping threats of our time. This paper examines the effect of student debt relief on individual credit and labor market outcomes. We exploit the plausibly-random debt discharge due to the inability of National Collegiate, the largest owner of private student loan debt, to prove chain of title for thousands of loans across the US. Using hand-collected lawsuits filings matched with individual credit bureau information, we find that borrowers experiencing the debt relief shock reduce their indebtedness by 26%, by both reducing their demand for credit and limiting the use of existing credit accounts, and are 12% less likely to default on other accounts. After the discharge, the borrowers' geographical mobility increases, as well as, their probability to change jobs and ultimately their income increases by more than \$4000, which is equivalent to about two months' salary. These findings speak to the benefits of intervening in the student loan market to reduce the consequences of debt overhang problems by forgiving student debts.

Keywords: Student Debt Forgiveness, Private Student Loans, Legal Settlement, Mobility, Debt Collection

JEL Classification: D14, H52, H81, J24, I23

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[†]Harvard Business School and NBER: mdimaggio@hbs.edu.

[‡]Department of Finance, Kelley School of Business, Indiana University: akalda@iu.edu.

[§]J. Mack Robinson College of Business, Georgia State University: wyao2@gsu.edu.

1. Introduction

Student debt has experienced a staggered growth in the last decade, reaching \$1.5 trillion in the first quarter of 2018 (NYFED, 2018). Since the Great Recession, student debt levels surpassed auto loans, credit card debt and home-equity lines of credit and currently only trail mortgage liabilities as the second largest consumer debt in the United States. Since 11 percent of borrowers are 90 days or more delinquent on their student debts, rising student debt is considered one of the creeping threats of our time. This situation has ignited a heated debate about potentially bringing relief to borrowers crippled by student debt, and policymakers have considered ways to keep the student loan problem from swelling out of control. The newly appointed Chairman of the Federal Reserve even stated that "As this goes on and as student loans continue to grow and become larger and larger, then it absolutely could hold back growth."

Federal student loans are directly funded by the government and offer numerous consumer protections such as income-based repayment options that help borrowers in need. However, many people with private student loans, like those who took on subprime mortgages, end up shouldering debt that they never earn enough to repay. These trends might have aggregate effects because about 44 million graduates hold student debt with amounts averaging more than \$30,000, and such burden might constrain borrowers' consumption and savings decisions. What exacerbates the situation is also a general lack of consensus on the policy objectives. For instance, they might be designed to target the liquidity constraints that have pushed the borrowers into distress, e.g. by relating the monthly repayments to borrowers' income. Alternatively, policymakers could implement interventions targeting the debt overhang problems associated with facing a significant debt burden, e.g. forgiving student loan principals altogether.¹ The empirical challenge in examining borrowers' behavior and potential reactions to changes in policies is to find plausibly exogenous variation in the borrowers' exposure to student debt and collect detailed information about the borrowers' decisions over time.

This paper overcomes these challenges in two ways. First, we have credit bureau data on borrowers' balance sheets, which provides information, such as monthly payments and loan amounts, on all type of accounts, but also provides employment and income information for a substantial sample of

¹See, for instance, the policy proposals recently discussed (https://www.forbes.com/sites/robertfarrington/2019/04/24/the-2020-presidential-candidates-proposals-for-student-loan-debt/1c74e147520e).

borrowers. Second, we exploit a plausibly exogenous debt relief shock experienced by thousands of borrowers due to the inability of the creditor to prove chain of title. Specifically, the largest holder of private student loan debt, National Collegiate with 800,000 private student loans totaling \$12 billion, and its collector agency, Transworld Systems, lost a series of collection lawsuits against the borrowers they were collecting from. National Collegiate bought the student loans from a series of banks and other financial institutions, but judges throughout the country have tossed out collection lawsuits by National Collegiate, ruling that it failed to establish the chain of title, because it was not able to prove it owned the debt on which it was trying to collect. This provides an ideal setting to explore the effects of relieving borrowers from debt overhang as the lack of documentation by National Collegiate is random and exogenous to borrowers' choices.

We hand-collected a unique dataset with information about these lawsuits, which provided us with details on the borrowers' identities, when these lawsuits were filed and adjudicated and in which court. This allowed us to then match this information to credit bureau data at household level in order to obtain a rich set of outcome variables for these borrowers. In order to isolate the effect of the student relief on these borrowers, we use a control group of borrowers living in the same ZIP Code, with the same age, a similar student loan amount to pay off, and most importantly, we restrict attention to borrowers that were also in default. Intuitively, we do not want to compare borrowers whose student debt was discharged to borrowers that were current on their debts. Instead, we only exploit the heterogeneity in the ownership of the student debt and the collection agency. We control for individual fixed effects as well as county by month fixed effects in this difference-in-differences setting to control for any time-varying local economic shocks.² Furthermore, we test and confirm the hypothesis that the treatment group and the control group are indistinguishable in the pre-period.

This setting provides us a unique opportunity to study the burden that defaulting on student loans represents for millions of individuals. We proceed by analyzing three main sets of outcome variables. First, we explore whether borrowers' leverage changes in the aftermath of the debt relief. We find that borrowers reduce their total liabilities, excluding the student loans object of the lawsuit, by about \$4,000. The results are consistent across accounts as they delever across all types of loans,

²A similar approach has been used by Mayer et al (2014) to study whether homeowners respond strategically to changes of mortgage modification programs induced by settlement of U.S. state government lawsuits against Countrywide Financial Corporation.

from credit cards to auto loans to home loans. We are also able to provide evidence that such adjustment happens along both the extensive and the intensive margins. In other words, the number of accounts decreases, and the balance on the existing account decreases as well, and this is mainly driven by higher repayments. Furthermore, we also show that borrowers reduce the number of inquiries, consistent with a lower demand for credit. Note that these borrowers were in default, so the effects we provide are not due to the cash-flow effect of having the monthly payment associated with the student debt becoming disposable income, i.e. they were not paying even before the legal settlement.

The second set of results pertain to borrowers delinquency. We test whether, having experienced relief from the student debt, these borrowers experience lower delinquency rates on other accounts. We find that the treated borrowers are significantly less likely to default on any type of account, an average decrease of about 12%, and in particular, they are less delinquent on credit cards and mortgages. Conditional on being delinquent, their past-due balance also decreases significantly by about \$400, which is a decrease of about 18%. These findings speak to the potential spillover effects across liabilities and to a potential indirect benefit of intervening in this market by helping borrowers unable to afford their student loan debts.

Another set of results involves mobility and income. We are able to trace the residence of these borrowers before and after the debt relief shock. Consistent with a debt overhang problem affecting these borrowers, we find that the treated individuals are significantly more likely to move when their student loans get discharged. These results hold for both ZIP Code level and state-level tests, which suggests that indeed these borrowers are more able to pursue opportunities elsewhere when relieved from the burden of their financial obligations. We further explore this dimension by analyzing whether the borrowers income increases in the aftermath of the debt discharge. For a more restricted sample of borrowers, we also observe the income from a proprietary database used for income and employment verification services. Consistent with the hypothesis that once their debt is discharged the borrowers are able to pursue better opportunities, we find that these borrowers' income increases by more than \$4000, which is roughly equivalent to two months' salary. This increase in income is likely due to the borrowers' ability to accept better jobs. We indeed find that treated borrowers are significantly more likely to change jobs with respect to the control group after the debt relief shock

and to accept higher-paying jobs.

Finally, we also explore whether eliminating the borrowers' debt also increase their spending ability. We should not expect all treated borrowers to react in the same way, specifically, there might be two separate groups of borrowers. On the one hand, there are borrowers who, due to income shocks or overspending, ended up defaulting on multiple accounts. On the other hand, there are also borrowers who only defaulted on their student loan. The two groups might exhibit different behavior because the latter group is more likely to experience a significant boost of their finances and to be able to get back on their feet after the lawsuit decision. Although we do not have a comprehensive measure of consumption, we can infer car purchases from the credit bureau information. We show that borrowers that were delinquent exclusively on their student debts are significantly more likely to increase their consumption after the court decision. As with the findings on decreased defaults, this evidence further shows that policy interventions in the student loan market should not be considered a zero-sum game between lenders and borrowers, as there might be wider implications for the economy.

Overall, our results shed novel light on the potentially adverse effects of the increase in student debt and of the corresponding defaults on individuals outcomes. Our findings suggest that the costs of the rising student debt burden on the new generations can indeed have important effect: student debt limits the borrowers' access to better opportunities and also has significant spillover effects to other debt classes.

Our evidence complements a recent strand of the literature showing that alleviating short-run liquidity constraints have a beneficial effects on individuals' behavior, by highlighting the role of long-run constraints. For instance, Ganong and Noel (2018) show that, in the context of the Home Affordable Modification Program (HAMP), principal write-downs had no impact on underwater borrowers, while lower monthly payments benefited borrowers. This is consistent with the evidence on the effects of lower monthly mortgage payments shown by Di Maggio et al. (2017) and Fuster and Willen (2017) and the literature on marginal propensity to consume out of transitory income shocks (e.g. Gross and Souleles, 2002, Johnson, Parker and Souleles, 2006, and Agarwal, Souleles and Liu, 2007). Our findings show that debt overhang might be a real issue facing millions of student loan borrowers, which significantly shapes their behavior. The difference might be due to the fact that student loan cannot be discharged in bankruptcy, while the other studies have focused on other types

of debts.³ Similar conclusions about the importance of debt overhang have recently been drawn in the context of credit card modification programs by Dobbie and Song (2019). Also related is a recent paper by Cheng, Severino and Townsand (2017), which explores how consumers fare outside of the court system when they negotiate directly with debt collectors.

Given its staggering growth and potential consequences on generation of young individuals, the student loan market has attracted increasing attention from academics.⁴ For instance, the level of student debt might have effects on human capital acquisition, in fact, Fos, Liberman and Yannelis (2018) analyze federal student loan borrowers in the US, and document a negative relationship between the level of undergraduate student debt and graduate school enrollment. Similarly, Scott-Clayton and Zafar (2016) investigate the effect of merit-based aid on future earnings and debt.

Also related are some recent studies on mobility. Bleemer, Brown, Lee and van der Klaauw (2017) provide evidence that in regions where many students are exposed to college costs, increased tuition is associated with more co-residence with parents and less living with roommates. While Goodman, Isen and Yannelis (2018) show that an increase in federal government lending has a significant effect on household formation early in the lifecycle, leads to a persistent increase in homeownership, with larger effects among those most financially constrained.

There are also few papers trying to understand the reasons behind the recent increase in the stock of student loans. It has been related to an increase in tuition across country and to the financial crisis. Specifically, Lucca, Nadauld, Shen (2018) establish a causal link between student loan availability and college tuition which has been the subject of policy discussion and debate for at least three decades (Bennett, 1987, for example), whereas Amromin, Eberly and Mondragon (2018) analyze the relationship between student loans and the housing market and estimate that, for every lost dollar of home equity credit that would have been used to nance college enrollment, households increase student loan debt by forty to sixty cents.

Overall, we believe our paper can offer a unique opportunity to investigate how the student loan burden affects the individuals' consumption and savings decisions as well as their income and employment prospects. In doing so, this paper also quantifies how valuable it is for these individuals

³Our paper is also related to the recent evidence showing the effects of bankruptcy protection, e.g. Dobbie, and Goldsmith-Pinkham, 2014, Dobbie and Song, 2015, and Dobbie, Goldsmith-Pinkham, and Yang 2017.

⁴See Avery and Turner (2012) for an early discussion of which students are more likely to borrow too much and those more likely to underinvest in college education.

to lift the constraints attached to an excessive debt burden.

The rest of the paper is organized as follows. Section 2 describes the data employed, the construction of the sample and the empirical strategy. Section 3 presents the main results of the paper. In an effort to better understand the borrowers mostly affected by debt relief, Section 4 explores whether our effects are heterogeneous depending on borrowers' characteristics, while Section 5 concludes.

2. Empirical Framework

This section first describes the source of our exogenous variation, then discusses the data sources and empirical methodology to measure the impact of debt discharge on borrowers' outcomes.

2.1. Court verdicts

National Collegiate is the largest private holder of student debt in the US with 800,000 private student loans, totaling \$12 billion.⁵ According to the Consumer Financial Protection Bureau investigation, more than \$5 billion of the debt held by National Collegiate was in default as of 2018. National Collegiate with its collection agency, Transworld System, have brought tens of thousands of lawsuits in the past five years across the country to aggressively pursue borrowers who fell behind on their bills. However, judges throughout the country have tossed out lawsuits by National Collegiate, ruling that it failed to establish the chain of title, because it was not able to prove it owned the debt on which it was trying to collect.

The issue arises from the fact that National Collegiate is not a lender, but rather it purchased loans made to college students a decade ago by dozens of different banks, which were bundled together by a financing company and sold to investors through securitization.⁶ But as the debt passed through many hands before landing in National Collegiate's trusts, critical paperwork documenting the loans' ownership disappeared for a subset of loans. In other words, National Collegiate's legal problems have hinged on its inability to prove it owns the student loans.

While valid affidavits must be signed by a witness with personal knowledge of the consumers' account records, the CFPB found that such affidavits didn't exist in many of the lawsuits. In fact,

⁵National Collegiate is an umbrella name for 15 trusts.

⁶These private loans were not guaranteed by the federal government.

Transworld employees completed and notarized sworn legal documents for lawsuits brought on behalf of the trusts, but these were ruled insufficient to prove ownership of the debt because the collector did not have personal knowledge of these records. In 2017, the CFPB fined the National Collegiate Student Loan Trusts, and its debt collector nearly \$22 million, charging them for aggressively suing students for debts that they allegedly couldn't prove were legitimate. These lawsuits rulings provide an ideal setting to identify the effects of debt relief on borrowers' outcomes, as they are arguably orthogonal with respect to the borrowers' characteristics.

2.2. Data

Our analysis relies on two unique data sources. First, to take advantage of the settlements as source of variation, we hand-collected information about all collection lawsuits initiated by National Collegiate or its collection agency, Transworld Systems, using a new platform provided by LexisNexis. Lawsuits against borrowers who have fallen behind on their consumer loans are typically filed in state or local courts, where records are often hard to search. This means that there is no national tally of just how often National Collegiate's trusts have gone to court. This required us to go through all filings related to the trusts and then select the ones related to the collection of student loan debt county by county. This allowed us to gather information about the identity of the defendants, the court in which the case was filed, the date of filing and adjudication. The data covers all civil courts in the US starting in 2010 and ending in 2017.

The second unique data is provided by Equifax Inc., one of the main credit bureaus, which allows us to construct the key outcome variables. The credit bureau provides information on households balance sheets, specifically, monthly payment history of all the borrowers' loans, including auto loans, mortgages, home equity lines of credit, student loans and credit cards (revolving). The data has granular information about the main features of these loans, such as date opened, account type, credit limits, monthly scheduled payment, balance, and performance history. It contains more than 200 million consumer credit files and over a billion credit trades, i.e. information about single loans,

⁷In one frequently cited ruling, Lovett v. National Collegiate Student Loan Trust 2004-1, a Florida appeals court held that the creditor, a securitized investment trust, had not submitted sufficient evidence to prove that it owned the note on a loan originated by Bank One in Chicago. The court overturned a summary judgment and returned the case to a lower court. At that point, the creditor withdrew the case.

and is updated monthly. Limited versions of this data have been employed in other papers studying households' financial decisions. However, our proprietary version is unique in a few respects.

First and foremost, to carry out our analysis, we need to be able to match the borrowers' information from the lawsuits to the credit bureau's information. The bureau matched the names and location of the borrowers with credit records by using both the names of the borrowers as well as the location and the existence of a defaulted student loan account on file. We verified the match by also making sure that the identified borrowers had student debt discharged after the decision date of the lawsuit. This resulted in about ten thousand borrowers for which we could match the legal information to the credit files.

Second, our data are not confined to households balance sheet information but include several other information about the borrowers. For a significant sample of borrowers including millions of individuals from more than 5,000 employers in the U.S., we observe their masked employer identity, as well as the industry they work in and their main occupation, through Equifax's proprietary employment data used in employment and income verification. For the same sample, we observe information on each employee's wages, and whether the employee remains employed at the firm at a given point in time. We also observe demographic information, such as the gender, whether the borrower is married and a college graduate, which is collected by creditors. Overall, we believe our data provide us with a unique opportunity to study the value of student debt relief on borrowers' credit outcomes and mobility.

2.3. Empirical methodology

Our empirical strategy consists of exploiting the individual court decisions as source of exogenous debt relief uncorrelated with borrowers' characteristics. Then, the individuals involved in the failed collection lawsuits constitute our treatment group and we can compare their outcomes before and after the debt discharge. Since this is likely to be a population of severely-constrained borrowers, we do not want to compare their behavior with borrowers that were current on their debts. Instead, we want to exploit the cross sectional variation provided by the fact that only the National Collegiate trust was the subject of these failed collection attempts.

Then, other borrowers that were similarly situated in default constitute a natural control group.

Specifically, we build our control group by gathering information about other individuals of the same age, carrying similar student loan amounts, who lived in the same ZIP Code and crucially, who defaulted on their student loans as well. In other words, our control group is other borrowers exposed to the same local economic conditions, with the same demographic characteristics, that also defaulted on their student debts, but whose loan was not held by National Collegiate, which resulted in their debt not being charged off. Having defined our treatment and control group, our main specification takes the following form:

$$Outcome_{i,j,t} = \alpha + \beta \times (Treated_i \times Post_t) + \mu_i + \gamma_{i \times t} + \varepsilon_{i,j,t}$$
 (1)

where the outcome variables range from defaults to leverage, to mobility and income; $Treated_i$ is a dummy that identifies the treated individuals who received the debt discharge; $Post_t$ is an indicator variable identifying the 36 months after the discharge and zero for the 36 months before, while μ_i and $\gamma_{i\times t}$ are individual and county by month fixed effects. The Post dummy is purposely capturing several months after the discharge because for some of our outcomes we would expect a lagged reaction. We cluster the standard errors at the ZIP Code level. To study how long it takes for the borrowers to react to the discharge, and to explicitly show that the treatment and the control group are indistinguishable before the discharge, we also estimate the following dynamic specification:

$$Outcome_{i,j,t} = \alpha + \sum_{\tau = -25}^{25} \beta_{\tau} \times (Treated_i \times Post_{\tau}) + \mu_i + \gamma_{i \times t} + \varepsilon_{i,j,t}$$
 (2)

so that we can plot the estimated coefficients β_{τ} with the corresponding confidence intervals. Since our sample consists of 24 months on either side of treatment, the dummy variable at both ends captures all months before or after that particular month, i.e. $\tau = 25$ ($\tau = -25$) captures all months after (before) 24 months from treatment.

2.4. Summary statistics

We begin our analysis by describing our sample in Table 1. Panel A reports the summary statistics for the main variables used in the analysis. There are 9.878 individuals in the treatment group and 118,772 in the control group. Our borrower \times month panel data contains about 6 million observations

when we restrict the credit report data to only three years before and after the treatment date. We find that on average these borrowers have about 7 credit accounts, which include any type of loan, and a total indebtedness level of about \$25,000, of which \$16,000 are not related to the student loans. The average credit card utilization is 34%, and they have on average about one account in delinquency status in addition to the student loan with an average \$2,200 past-due amount. Finally, the average monthly salary is \$2300. In order to discuss how the borrowers in our sample compare to the average borrower, Panel B reports key statistics from four different samples: a 1% random consumer credit panel, a sample of the student loan population, the subset of borrowers having student loans in delinquency and finally our sample of treated individuals. We find that our sample has the highest amount of debt outstanding with about \$49,900, they have the lowest number of credit card accounts, 3 versus an average of 11 of the general population and the lowest fraction of mortgages, which is also indicative of our sample being younger (34 years compared to 49 of the consumer credit panel). They also exhibit an average of 5 accounts past-due with an average \$6,000 past-due amount, compared to about 0.4 accounts and \$1,400 of the general population. While there are significant differences with the average borrower, in many respects, our sample of treated individuals is similar to the delinquent student loan population, e.g. total debt, number of accounts. and age. The most notable differences are the higher credit card balance of our sample, but lower mortgage and auto balance compared to the benchmark sample. Overall, these comparisons show that, as we would expect, our treatment sample is on average more constrained, younger and has lower assets than that of the average borrower.

To complement the previous statistics, we also investigate the geographical distribution of these borrowers across the US. Panel A of Figure 1 plots a heat map of the US showing the geographical distribution of delinquent student loan borrowers based on a random sample of the credit bureau data. It shows that the delinquency is quite spread out across the US but with a higher incidence in California, Texas and Florida. Panel B of Figure 1, instead, shows the geographical concentration of our treated individuals which are similarly present across several states in the US. Figure 2 complements the previous one by plotting the number of lawsuits settlements matched to the credit file over our sample period. We find that these are present throughout the sample but spike during the 2014-2017 period.

3. Main Results

This section describes the main results of the paper distinguishing between the effects of the discharge on leverage, delinquencies, mobility and income.

3.1. (De)Leveraging

The first hypothesis we analyze is whether the sudden student debt discharge affects the borrowers' behavior with their other credit accounts, as an indication of their financial health post-discharge. On the one hand, the discharge has a wealth effect but does not increase the disposable income of these borrowers, and so it might have limited effects. On the other hand, borrowers might be trying to improve their financial situation after getting this break to avoid ending up in similar trouble in the future.

Table 2 examines the effect of the debt discharge on leverage. Columns (1) to (4) control for individual fixed effects and month fixed effects, while Column (5) through (8) also include countymonth fixed effects, which allows us to control for any time-varying differences between regions. The first step towards a better understanding of how the affected borrowers change their leverage is to examine the extensive margin, that is, whether they tend to change their number of accounts. When we consider their total number of accounts (Column 1 and 5) and their number of accounts other than the student loans (Columns 2 and 6), we find that they significantly decrease. On the intensive margin, we also find that the total debt of the borrowers that experienced the discharge is significantly lower than that of the control group. Columns (3)-(4) and (7)-(8) show that both when we consider total debt and when we exclude the student loans, borrowers reduce their indebtedness by about four thousand dollars. Given an average indebtedness level of \$15,317 in the pre-period, this corresponds to a 26 percent reduction.

Although the result of the legal disputes should be orthogonal to borrowers' behavior, an important assumption of our analysis is that the treatment and the control group were on parallel trends in the pre-period. Panel A of Figure 3 shows that this is indeed the case. It plots the dynamic coefficients of our baseline regression and shows that, while the treatment and the control group are indistinguishable from each other in the pre-period, the treated borrowers tend to dramatically reduce their total debt (excluding the student loan discharged) right after it gets discharged, and they continue doing so for several months after the event. Note that there might be few weeks delay between the court decision and the date when the discharge is reported in the credit report. Panel B and C also differentiate between the effect for the borrowers experiencing the discharge in the first half of the sample and in the second half. Although, we find that the total debt significantly decrease for both subsamples, the effect is strongest for the first half of the sample.

We can further study how borrowers' leverage evolves by differentiating among the various kind of debts, i.e. credit cards, auto loans and mortgages. Panel A of Table 3 looks at the effects on the number of different accounts. We find that consistently across all debt categories, and both with and without county-month fixed effects, the treated borrowers are significantly more likely to reduce the number of accounts. Panel B of Table 3 explores the intensive margin and shows that on average the credit card debt is reduced by at least \$350, their auto loans decline by about \$300 and their mortgages decrease by about \$1,000. Overall, these findings suggest that treated individuals are significantly more likely to reduce their leverage after the debt is discharged.

Next, we examine in Table 4 how this deleveraging occurs. Panel A focuses on credit cards, Panel B on auto loans and Panel C on home loans. Columns (1) and (4) of Panel A show that the borrowers are significantly less likely to open an account. Columns (2) and (5) provide evidence that treated borrowers tend to use the existing accounts less as their utilization decreases by 2%, which is equivalent to a 6-percent reduction with respect to the average of 34%. Columns (3) and (6) show that deleveraging is also partially driven by an increase in repayment above the minimum payment. We complement these results by examining the dynamics of this behavior in Figure 4, which focuses on revolving utilization and shows that while there is no significant difference in the utilization ratio between borrowers that get their loans discharged and those who do not in the pre-period, we find that there is significant wedge right after the legal decision.

Panel B examines whether the borrowers' behavior for auto loans is any different. Similarly to Panel A, we look at the account opening and payments, but rather than utilization, we examine the response in the origination amount. We find that in the case of auto loans, most of the effects are driven by smaller auto loans compared to the control group, with a reduction of about \$600. Panel C shows a similar pattern for mortgages after the student debt is discharged: treated borrowers exhibit

significantly smaller mortgages, with an average effect of almost \$10,000.

Finally, we can exploit the richness of our data to show that these results are driven by the borrowers' deliberate choice of reducing their demand for credit by analyzing credit inquiries. Our data contain a number of hard inquiries for any credit application. We focus on the number of inquiries in the past 90 days and on an indicator for multiple inquiries as main dependent variables. We can then test whether the borrowers demand more credit after their student loans get discharged. Table 5 shows that treated individuals reduce their demand for credit as the number of credit inquiries decreases significantly after the discharge.

Overall, these results provide evidence that one of the effects of relieving borrowers from their student loans is to allow them to better manage their finances and start significantly deleveraging which is likely to make them more resilient to negative shocks.

3.2. Delinquency

A natural question at this point is whether the treated individuals are likely to end up in default again after the discharge. On the one hand, the findings discussed above would suggest that the lower leverage relative to the control group would reduce the likelihood to being delinquent on their accounts. On the other hand, the borrowers that ended up in default the first time around might be more likely to be subject to similar negative shocks in the future and, since they are likely credit-constrained, they might find themselves unable to meet their obligations again.

We test this hypothesis in Table 6. Panel A investigates the extensive margin, i.e., whether the borrowers are likely to default, by differentiating between total delinquency (which excludes the student loans) and being delinquent on credit cards, auto loans or mortgages. Columns (1)-(4) control for individual and month fixed effects, while the most conservative specifications including county-month fixed effects are reported in Columns (5)-(8).

By comparing the results across accounts, we find that treated individuals are 12% less likely to experience any type of default in the post period. Most of this effect comes from a significant reduction, about 11%, in the likelihood of being delinquent on credit cards payments. While we do not find a statistically significant effect on auto loans, the effect for mortgages is statistically significant but smaller in magnitude. Figure 5 reports the dynamic coefficients for the probability

of being delinquent on any account (except the student loans subject of the collection attempt by National Collegiate). We find that, although treatment and control group exhibit a very similar delinquency behavior for a long period of time before the discharge, about three months after it, the treated borrowers are significantly less likely to be delinquent on any account. This reassures us about our identification strategy and shows that the effects we find are quite consistent and economically significant for the treated individuals.

Panel B quantifies these effects by looking at the delinquency amounts. We find that on average the treated borrowers exhibit about \$400 lower delinquency amount, which is equivalent to a 20% reduction. While there is no significant difference in auto loans, we find that credit card delinquency declines by \$60, while mortgage delinquency decreases by about \$400.

All in all, we find further evidence that the borrowers significantly improve their financial conditions in the aftermath of their student loan being discharged, as they have lower debt and are significantly less likely to being in default.

3.3. Mobility and Income

Having established that borrowers whose student debt is discharged are able to improve their credit outcomes, we now investigate whether the discharge also improves their real outcomes. One of the key channel through which student debt relief might improve borrowers' situation is by reducing the extent to which these borrowers face debt overhang problems. Specifically, after the debt being discharged, borrowers might have more flexibility in pursuing other jobs and potentially better opportunities. This hypothesis has been at the forefront of the policy debates about the costs of rising tuition costs and of student debts being out of control.

We test this hypothesis in two ways. First, Table 7 presents the estimated coefficients from our baseline regressions using mobility as dependent variable. We should expect the court decision to be significantly more beneficial for those borrowers who only defaulted on student debt, because once that get discharged, they are relieved from debt overhang problems altogether. Instead, for borrowers that are delinquent on multiple accounts, the court decision still leave them on the hook for the rest of their liabilities. Then, Table 7 differentiate between these two subsamples. In Panel A, we measure mobility as whether the state of residence associated to the borrowers' changes in the aftermath of

the debt discharge. Similarly to the previous tables, we report estimates for specifications where we control for individual fixed effects (Columns 1 and 3) and for county-month fixed effects (columns 2 and 4). Consistently across specifications, we find that borrowers that see their student loan discharged are significantly more likely to move. The effects are both statistically and economically significant; in fact, the treated borrowers are about 4% more likely to move to a different state in the post period than similar borrowers that still suffer from the student loan burden. Figure 6 reports the dynamic coefficients for the borrowers' mobility. Although noisier than the previous specifications, we find that the pre-trends confirm that borrowers are not different in their mobility before the discharge, but mobility trends upwards for the treated individuals in the aftermath of the discharge.

A complementary way of investigating whether treated borrowers are able to improve their economic conditions is to exploit the granularity of our data, for a restricted sample of borrowers, to test if borrowers' employment changes. Although the test is low-powered due to the lower number of observations, Panel B of Table 7 provides evidence that this is indeed the case: borrowers whose student debt gets discharged are more likely to change jobs, especially if they were only in default on their student loans. Panel C and D complement these results by showing that these borrowers are more likely to move to a new industry and, more importantly, to a higher paying industry.

Table 8 complements the previous findings by quantifying the increased income that borrowers, who are not constrained by student debt anymore, are able to achieve in the aftermath of the discharge. We find that treated borrowers do exhibit higher income in the post period compared to the control group by about \$100. We can use this estimate to quantify the cumulative income gained over the three years after discharge to be \$111.82*37 = \$4,137.34. This is a pretty substantial gain as it is equal to almost two months' salary for the average individual in our sample. These findings strongly suggest that the increase in student loans burden for young borrowers might be an important drag on their economic outcomes by limiting their ability to pursue better opportunities. Overall, we find that treated borrowers are more likely to change home, job and earn more. If on the one hand these are the costs of the looming student debt crisis, these findings can also inform the debate about the potential benefits of intervening in this market.

3.4. Additional Results

A natural question at this point is to see whether there is any expansionary effect of the debt discharge. Although we do not have a comprehensive consumption measure, we can follow the existing literature and use car purchases as a proxy for durable consumption. The idea being that after the debt discharge these borrowers are more likely to be able to afford a car purchase, both because of the increased income that we have documented and because of the easier access to credit. Table 9 reports in Columns (1) and (2) the effect of debt relief on car purchases for borrowers that only defaulted on their student loans, while Columns (3) and (4) show the same analysis for borrowers with multiple accounts in default. We find that the least constrained borrowers do increase their consumption in the aftermath of the debt relief.

Another hypothesis we can test is whether experiencing debt relief allows these borrowers to continue or extend their studies. We do not observe information about their education, however, we can test it indirectly by investigating whether these borrowers are more likely to obtain a new student loan. Table 10 reports the results. We indeed find that only those that defaulted exclusively on student loans are more likely to get a new one after the debt relief. Notice that these new loans are not used as a refinancing tool of their existing liabilities but are actually new accounts opened that do not coincide with the closing of other student loan accounts. This evidence might also provide a channel explaining the results on the higher mobility and ultimately higher income for these borrowers: after the debt relief these borrowers not only improve their finances, but improve their education, which ultimately allows them to seize better opportunities.

4. Heterogeneity

We complement the previous analysis by exploring whether our results depend on borrowers' characteristics. First, borrowers of different ages might respond very differently to the debt relief shock. For instance, older borrowers might be more likely to try to quickly improve their finances in light of a closer retirement, or to have a different propensity to move to take advantage of better job opportunities. This hypothesis is also related to the standard models of life cycle behavior such as Browning and Crossley (2001). We can formally test this hypothesis in Panel A of Ta-

ble 11, where we modify our baseline specification by interacting the main coefficient, Debt Relief $\times Post, with an indicator that identifies borrowers older than the median (35 years). The dependent variables are total dependent variables are total dependent variables. The dependent variables are total dependent variables are total dependent variables. The dependent variables are total dependent variables are total dependent variables. The dependent variables are total dependent variables are total dependent variables are total dependent variables. The dependent variables are total dependent variables are total dependent variables. The dependent variables are total dependent variables are total dependent variables are total dependent variables. The dependent variables are total dependent variables are total dependent variables are total dependent variables. The dependent variables are total dependent variables are total dependent variables are total dependent variables. The dependent variables are total dependent variables are total dependent variables are total dependent variables. The dependent variables are total dependent variables are total dependent variables are total dependent variables. The dependent variables are total dependent variables are total dependent variables are total dependent variables. The dependent variables are total dependent variables are total dependent variables. The dependent variables are total dependent variables are total dependent variables are total dependent variables. The dependent variables are total dependent variables are total dependent variables are total dependent variables. The dependent variables are total dependent variables are total dependent variables are total dependent variables. The dependent variables are total dependent variables are total dependent variables are total dependent variables. The dependent variables are total dependent vari$

An additional source of heterogeneity that we exploit is the level of the total indebtedness, excluding the student loans, which proxies for the extent to which these borrowers are constrained. Panel B of Table 11 shows that this is indeed an important source of heterogeneity. More constrained households tend to reduce their total outstanding debts by almost \$8,000 and in particular their mortgage balance by about \$1,400. Similarly, we find that they also tend to reduce their credit card utilization by about 4%. Overall, this deleveraging makes them less likely to default on any other account after the debt relief shock. The effects are both statistically and economically significant, with a reduction in defaults of about 8%. Overall, the heterogeneity of these results can be informative of the sub-population more likely to experience the biggest benefits of a potential debt relief program.

5. Conclusion

A crisis in the student loan market has been looming over the economy, due to an explosion in recent graduates' indebtedness since the Great Recession and a worrisome increase in delinquency. Several policies have been advocated to help borrowers unable to meet their financial obligations, especially in the private student loan market, which is usually tapped by more fragile borrowers attending for-profit institutions and experiencing lower returns to education. Although these issues have spurred growing interests, we still know very little about what would be the benefits of offering some type of debt relief to borrowers in need. Furthermore, policy makers would need guidance on the type of policies that are likely to be effective in this market, from those addressing the immediate liquidity constraints of some of these borrowers to more ambitious policies aimed to forgive a portion of their debts. The main challenge faced by the existing literature has been the inability to observe detailed information about borrowers' balance sheets and decisions over time coupled with the difficulty to infer the causal link between debt and behavior due to the lack of plausibly-exogenous variation in the data.

This paper overcomes these challenges by taking advantage of the debt discharge that affected thousands of borrowers across the US due to the inability of National Collegiate to prove chain of title of the debts and by matching hand-collected lawsuits filings with individual credit bureau information. This allows us to build a unique panel dataset enabling us to estimate the effects of debt relief on borrowers.

We find that the borrowers experiencing the debt relief shock are significantly more likely to engage in deleveraging, by both reducing their demand for credit and limiting the use of the existing accounts. That is, borrowers benefiting from a debt relief seem to quickly try to improve their financial conditions. These efforts are successful in that they are also significantly less likely to default on their accounts, above and beyond their student loan accounts. These findings speak to the potential spillover effects across borrowers' liabilities and to an indirect benefit of intervening in the student loan market by helping borrowers unable to afford their student loan debts. Finally, debt relief helps these borrowers to overcome debt overhang constraints as they are significantly more likely to move, change job and experience a significant increase in income, which is equivalent to about two months' salary. Overall, these findings speak to the forceful impact that interventions in this market could have on these individuals.

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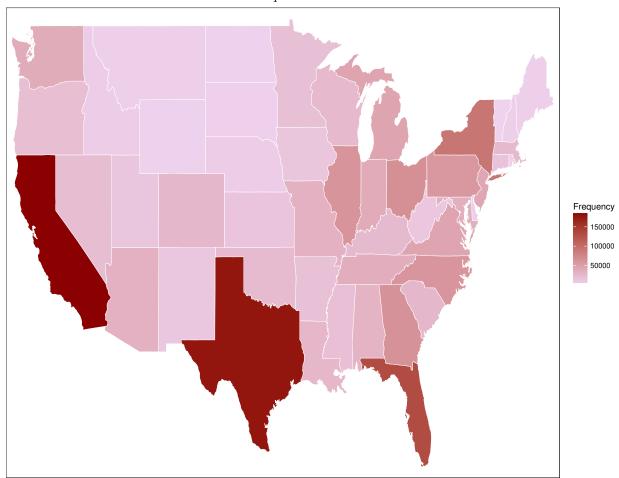
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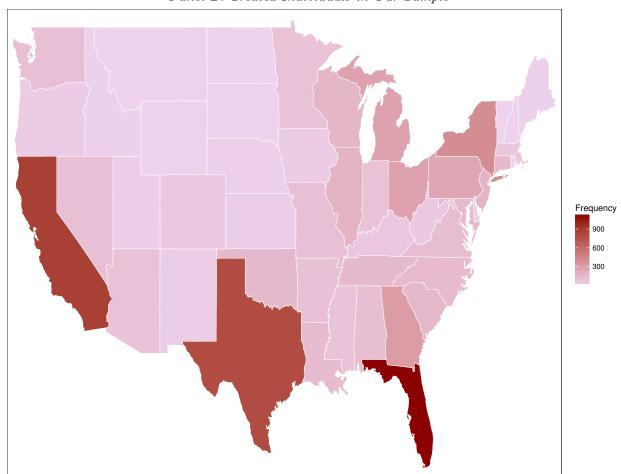
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Figure 1. Geographical Distribution of the Delinquent Student Loan Borrowers

The figures plot geographic distribution, at state level, of student loan borrowers. In Panel A, we plot total number of delinquent student loan borrowers based on complete credit bureau data. In Panel B, we plot number of treated individuals in our sample, who had delinquent student loans, but received debt relief due to favorable court rulings.



Panel A: All Delinquent Student Loan Borrowers



Panel B: Treated Individuals in Our Sample

Figure 2. Number of Legal Settlements

The figure plots number of legal settlements over time. Y axis is the number of legal settlements we hand-collected from court cases. X axis is the court ruling month.

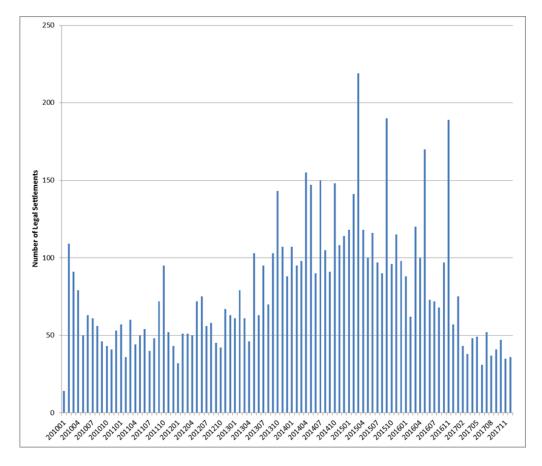
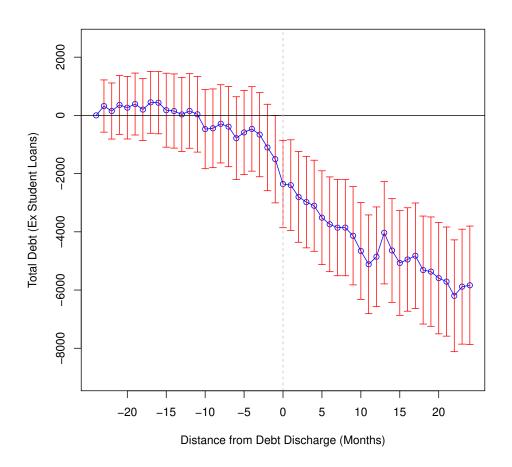


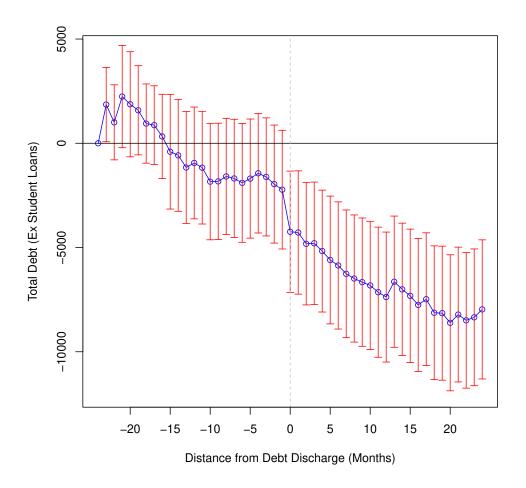
Figure 3. Dynamics of the Total Debt

The figure plots the coefficients on the interaction term of treated borrower indicator and relative monthly dummies from regressions specified in Equation (2). Relative monthly dummies are defined as the interval, in months, from the debt discharge date to credit report date. Dependent variable is total debt balance. On the right hand side, we control for individual fixed effects and county \times month fixed effects. Standard errors are clustered at ZIP Code level. The regression is based on borrower \times month panel data that contains both treatment and control groups.

Panel A: All Individuals in the Sample



Panel B: Individuals Treated in the First Half of the Sample and Controls



Panel C: Individuals Treated in the Second Half of the Sample and Controls

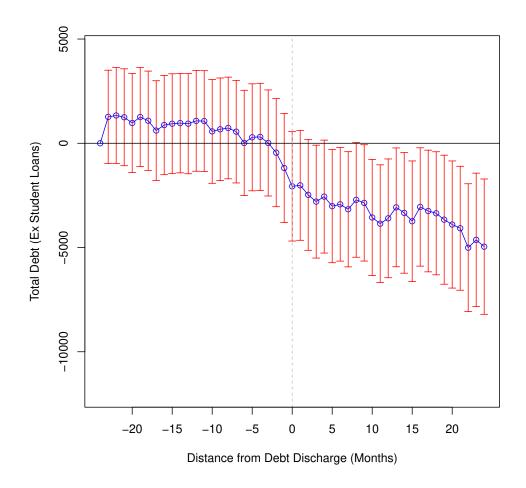


Figure 4. Dynamics of the Revolving Utilization

The figure plots the coefficients on the interaction term of treated borrower indicator and relative monthly dummies from regressions specified in Equation (2). Relative monthly dummies are defined as the interval, in months, from the debt discharge date to credit report date. Dependent variable is revolving utilization, calculated as ratio of revolving balance to revolving credit limit. It varies between 0 and 1. On the right hand side, we control for individual fixed effects and county \times month fixed effects. Standard errors are clustered at ZIP Code level. The regression is based on borrower \times month panel data that contains both treatment and control groups.

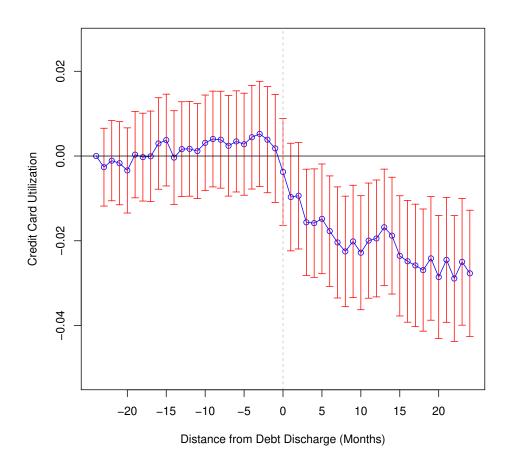


Figure 5. Dynamics of Delinquency Rate

The figure plots the coefficients on the interaction term of treated borrower indicator and relative monthly dummies from regressions specified in Equation (2). Relative monthly dummies are defined as the interval, in months, from the debt discharge date to credit report date. Dependent variable is the indicator of borrower having any delinquent account. On the right hand side, we control for individual fixed effects and county \times month fixed effects. Standard errors are clustered at ZIP Code level. The regression is based on borrower \times month panel data that contains both treatment and control groups.

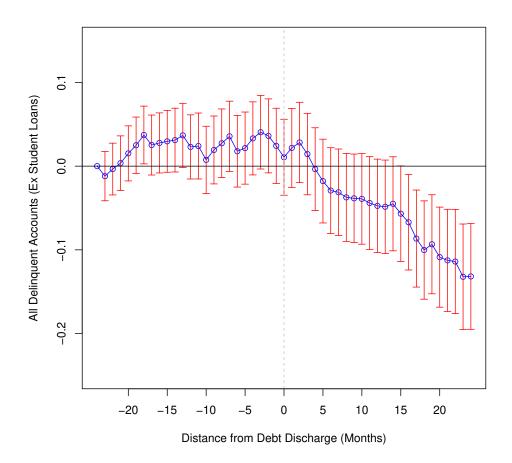


Figure 6. Dynamics of Mobility

The figure plots the coefficients on the interaction term of treated borrower indicator and relative monthly dummies from regressions specified in Equation (2). Relative monthly dummies are defined as the interval, in months, from the debt discharge date to credit report date. Dependent variable is the indicator of borrower moving from one address to another month to month. On the right hand side, we control for individual fixed effects and county \times month fixed effects. Standard errors are clustered at ZIP Code level. The regression is based on borrower \times month panel data that contains both treatment and control groups.

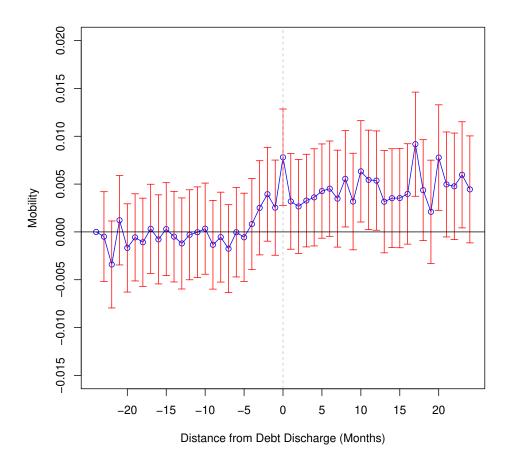


Table 1: Summary Statistics

This table reports summary statistics of individual borrower \times month panel data. We hand-collected a set of borrowers who received student debt relief due to court rulings against national Collegiate and its collector agency, Transworld Systems. We consider a control group of borrowers living in the same ZIP Code, with the same age, a similar student loan amount to pay off, and most importantly, we restrict the control group borrowers that were also in default. Our sample contains both the treatment and control groups, excluding loans with missing credit score, missing total balance, missing number of accounts, and invalid loan balance (negative or zero). In Panel A, we report statistics for the main variables used in the analysis. All the variables are from credit report data from one of the credit bureaus. In Panel B, we compare the credit attributes of our sample with a random sample of the population and with the average borrowers with student loans. Statistics for all borrowers are based on 1% Consumer Credit Panel (CCP).

Panel A: Statistics of the Sample

Variable	Mean	St. Dev.	Min	Median	Max
Number of Accounts	6.599	4.704	0	5	25
Total Debt (\$)	25,690.01	39,779.00	0	12,652	293,080
Total Debt (Ex Student Loans, \$)	16,300.29	$130,\!076.15$	0	7,930	293,080
Number of Accounts (Ex Student Loans)	2.901	3.284	0	2	25
Credit Card Accounts	2.116	2.589	0	1	13
Auto Accounts	0.538	0.757	0	0	3
Mortgage Accounts	0.115	0.421	0	0	3
Credit Card Balance (\$)	1,132.53	2,431.23	0	0	18,017
Auto Balance (\$)	3,943.34	7,021.75	0	0	31,877
Mortgage Balance (\$)	4,422.04	$22,\!359.52$	0	0	$175,\!443$
Credit Card Utilization	0.341	0.338	0	0.258	1
Auto Loan Origination Amount (\$)	20,629.78	12,724.36	550	17,339	77,868
Mortgage Origination Amount (\$)	214,839.02	186,797.58	22,900	154,777	507,750
All Delinquent Accounts (Ex Student Loans)	1.302	1.864	0	1	17
Total Past-Due Amount (Ex Student Loans, \$)	2,213.92	4,891.69	0	907	$54,\!455$
Mobility $(1/0)$	0.035	0.183	0	0	1
Income (\$)	2,376.71	1,636.62	830.21	2,531.19	9,588.85
Credit Score	535.25	74.44	300	530	836

Panel B: Different Population and Samples

	All	All	Delinquent	Sample	
	Borrowers	Student	Student	Treated	
	(1% CCP)	Loan	Loan	Individuals	
		Population	Population		
Number of Accounts	11.23	11.26	8.90	9.29	
Total Debt (\$)	$22,\!271.52$	$36,\!105.21$	40,634.51	49,943.09	
Credit Card Accounts	11.84	11.28	4.61	2.96	
Auto Accounts	0.95	1.09	0.78	0.63	
Mortgage Accounts	0.80	0.71	0.23	0.19	
Credit Card Balance (\$)	51.78	134.70	269.37	1829.39	
Auto Balance(\$)	16,954.98	16,595.81	$14,\!353.55$	4,464.43	
Mortgage Balance (\$)	186,211.67	194,967.58	134,257.00	6,469.94	
Credit Card Utilization	0.43	0.64	0.98	0.37	
Delinquent Accounts	0.44	0.83	3.44	5.15	
Total Past-Due Amount (\$)	1,471.48	2,580.82	14,847.59	6,028.63	
Age	49.32	37.79	39.52	34.75	
Observations	179,877,691	44,427,421	1,781,741	$438,\!117$	

Table 2: Student Debt Relief and Total Debt

This table reports results from difference-in-differences regressions of consumer credit outcomes based on borrower-month panel data. The dependent variable is the column title: total number of accounts in Columns (1) and (5); number of accounts excluding student loans in Columns (2) and (6); total debt balance in Columns (3) and (7); total debt balance excluding student loans in Columns (4) and (8). DebtRelief is defined as 1 for the delinquent student loans who received debt relief and 0 otherwise. Post is defined as 1 for 36 months after the debt relief and 0 for 36 months before the debt relief. On the right hand side, we control for individual fixed effects in all columns. Additionally, we control for credit report month fixed effects in Columns (1)–(4) and county × month fixed effects in Columns (5)–(8). Standard errors are clustered at ZIP Code level. The regression is based on borrower × month panel data that contains both treatment and control groups. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Dependent Var	No of Accounts	No of Accounts (Ex. Stud)	Total Debt	Total Debt (Ex. Stud)	No of Accounts	No of Accounts (Ex. Stud)	Total Debt	Total Debt (Ex. Stud)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$DebtRelief \times Post$	-0.79***	-0.39***	-4,506.6***	-4,017.7***	-0.76***	-0.36***	-4,398.8***	-4,943.9***
	(0.04)	(0.02)	(346.17)	(598.43)	(0.04)	(0.02)	(355.04)	(639.94)
$\begin{array}{l} \text{Individual FE} \\ \text{Month FE} \\ \text{County} \times \text{Month FE} \end{array}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	Yes	Yes	Yes	Yes	No	No	No	No
	No	No	No	No	Yes	Yes	Yes	Yes
Observations R ²	6,010,381	6,010,381	6,010,381	6,010,381	6,010,381	6,010,381	6,010,381	6,010,381
	0.82	0.85	0.8	0.15	0.86	0.88	0.84	0.21

Table 3: Student Debt Relief and Components of Debt

This table reports results from difference-in-differences regressions of consumer debt outcomes based on borrower-month panel data. In Panel A, the dependent variables are number of different accounts: number of credit cards in Columns (1) and (4); number of auto accounts in Columns (2) and (5); number of mortgage accounts in Columns (3) and (6). In Panel B, the dependent variables are total balance of different accounts: balance of credit cards in Columns (1) and (4); balance of auto accounts in Columns (2) and (5); balance of mortgage accounts in Columns (3) and (6). DebtRelief is defined as 1 for the delinquent student loans who received debt relief and 0 otherwise. Post is defined as 1 for 36 months after the debt relief and 0 for 36 months before the debt relief. On the right hand side, we control for individual fixed effects in all columns. Additionally, we control for credit report month fixed effects in Columns (1)–(3) and county × month fixed effects in Columns (4)–(6). Standard errors are clustered at ZIP Code level. The regression is based on borrower × month panel data that contains both treatment and control groups. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Panel A: Extensive Margin

Dependent Var	Credit Card	Auto	Mortgage	Credit Card	Auto	Mortgage
	Accounts	Accounts	Accounts	Accounts	Accounts	Accounts
	(1)	(2)	(3)	(4)	(5)	(6)
$DebtRelief \times Post$	-0.35***	-0.03***	-0.03***	-0.33***	-0.03***	-0.02***
	(0.02)	(0.01)	(0.00)	(0.02)	(0.01)	(0.00)
$\begin{array}{l} \text{Individual FE} \\ \text{Month FE} \\ \text{County} \times \text{Month FE} \end{array}$	Yes	Yes	Yes	Yes	Yes	Yes
	Yes	Yes	Yes	No	No	No
	No	No	No	Yes	Yes	Yes
Observations R ²	6,010,381	6,010,381	6,010,381	6,010,381	6,010,381	6,010,381
	0.83	0.76	0.85	0.86	0.81	0.89

Panel B: Intensive Margin

Dependent Var	Credit Card Balance	Auto Balance	Mortgage Balance	Credit Card Balance	Auto Balance	Mortgage Balance
	(1)	(2)	(3)	(4)	(5)	(6)
$DebtRelief \times Post$	-386.51*** (27.60)	-276.66*** (66.47)	-982.05*** (154.83)	-387.47*** (28.47)	-237.77** (67.80)	-867.41*** (161.22)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	No	No	No
County \times Month FE	No	No	No	Yes	Yes	Yes
Observations P ²	6,010,381	6,010,381	6,010,381	6,010,381	6,010,381	6,010,381
\mathbb{R}^2	0.68	0.59	0.79	0.74	0.67	0.84

Table 4: How Do Individuals Reduce Debt?

This table reports results from difference-in-differences regressions of consumer debt strategies based on borrower-month panel data. In Panel A, the dependent variables are changes in credit card accounts: number of accounts opening in Columns (1) and (4); revolving utilization in Columns (2) and (5); monthly payment in Columns (3) and (6). In Panel B (C), the dependent variables are changes in auto (home) accounts: number of accounts opening in Columns (1) and (4); origination amount in Columns (2) and (5); monthly payment in Columns (3) and (6). DebtRelief is defined as 1 for the delinquent student loans who received debt relief and 0 otherwise. Post is defined as 1 for 36 months after the debt relief and 0 for 36 months before the debt relief. On the right hand side, we control for individual fixed effects in all columns. Additionally, we control for credit report month fixed effects in Columns (1)–(3) and county × month fixed effects in Columns (4)–(6). Standard errors are clustered at ZIP Code level. The regression is based on borrower × month panel data that contains both treatment and control groups. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Panel A: Credit Cards	3					
Dependent Var	Account Opening	Utilization	Payment	Account Opening	Utilization	Payment
	— Opening			Opening		
	(1)	(2)	(3)	(4)	(5)	(6)
$DebtRelief \times Post$	-0.003*** (0.001)	-0.022*** (0.004)	16.66*** (1.42)	-0.002** (0.001)	-0.020*** (0.004)	15.37*** (1.51)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	No	No	No
$County \times Month FE$	No	No	No	Yes	Yes	Yes
Observations	6,010,381	6,010,381	1,299,622	6,010,381	6,010,381	1,299,622
\mathbb{R}^2	0.095	0.607	0.58	0.245	0.707	0.73
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Panel B: Auto Loans						
Dependent Var	Account Opening	Origination Amount	Payment	Account Opening	Origination Amount	Payment
	(1)	(2)	(3)	(4)	(5)	(6)
$DebtRelief \times Post$	0.001	-766.25***	11.96***	0.001	-627.76***	10.74**
	(0.00)	(183.09)	(3.11)	(0.001)	(192.57)	(5.28)
$\begin{array}{l} \text{Individual FE} \\ \text{Month FE} \\ \text{County} \times \text{Month FE} \end{array}$	Yes	Yes	Yes	Yes	Yes	Yes
	Yes	Yes	Yes	No	No	No
	No	No	No	Yes	Yes	Yes
Observations R ²	6,010,381	2,042,908	1,291,613	6,010,381	2,042,908	1,291,613
	0.08	0.73	0.75	0.23	0.82	0.84

Panel C: Home Loans						
Dependent Var	Account Opening	Origination Amount	Payment	Account Opening	Origination Amount	Payment
	(1)	(2)	(3)	(4)	(5)	(6)
$DebtRelief \times Post$	0.0001	-9,573.86***	22.79***	-0.0004	-9,013.09**	34.76**
	(0.0003)	(3,270.92)	(9.55)	(0.0004)	(3,738.62)	(17.04)
$\begin{array}{l} {\rm Individual\ FE} \\ {\rm Month\ FE} \\ {\rm County\ \times\ Month\ FE} \end{array}$	Yes	Yes	Yes	Yes	Yes	Yes
	Yes	Yes	Yes	No	No	No
	No	No	No	Yes	Yes	Yes
Observations R ²	6,010,381	2,042,908	1,291,613	6,010,381	2,042,908	1,291,613
	0.16	0.89	0.73	0.36	0.95	0.89

Table 5: Student Debt Relief and Credit Inquiries

This table reports results from difference-in-differences regressions of consumer debt strategies based on borrower-month panel data. The dependent variable is number of inquiries in the past 90 days in Columns (1) and (3) and an indicator of multiple inquiries in Columns (2) and (4). DebtRelief is defined as 1 for the delinquent student loans who received debt relief and 0 otherwise. Post is defined as 1 for 36 months after the debt relief and 0 for 36 months before the debt relief. On the right hand side, we control for individual fixed effects in all columns. Additionally, we control for credit report month fixed effects in Columns (1)–(2) and county \times month fixed effects in Columns (3)–(4). Standard errors are clustered at ZIP Code level. The regression is based on borrower \times month panel data that contains both treatment and control groups. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Dependent Var	Total Inquiries	Multi-Inquiry Indicator	Total Inquiries	Multi-Inquiry Indicator
	(1)	(2)	(3)	(4)
$DebtRelief \times Post$	-0.23*** (0.050)	-0.02*** (0.004)	-0.23*** (0.050)	-0.02*** (0.004)
Individual FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	No	No
County \times Month FE	No	No	Yes	Yes
Observations R ²	6,010,381 0.58	6,010,381 0.51	6,010,381 0.66	6,010,381 0.57

Table 6: Student Debt Relief and Delinquency

This table reports results from difference-in-differences regressions of consumer delinquency outcomes based on borrower-month panel data. In Panel A, the dependent variables are number of delinquent accounts: number of all delinquent accounts excluding student loans in Columns (1) and (5); number of delinquent credit card accounts in Columns (2) and (6); number of delinquent auto accounts in Columns (3) and (7); number of delinquent mortgage accounts in Columns (4) and (8). In Panel B, the dependent variables are balance of delinquent accounts: balance of all delinquent accounts excluding student loans in Columns (1) and (5); balance of delinquent credit card accounts in Columns (2) and (6); balance of delinquent auto accounts in Columns (3) and (7); balance of delinquent mortgage accounts in Columns (4) and (8). DebtRelief is defined as 1 for the delinquent student loans who received debt relief and 0 otherwise. Post is defined as 1 for 36 months after the debt relief and 0 for 36 months before the debt relief. On the right hand side, we control for individual fixed effects in all columns. Additionally, we control for credit report month fixed effects in Columns (1)–(4) and county \times month fixed effects in Columns (5)–(8). Standard errors are clustered at ZIP Code level. The regression is based on borrower × month panel data that contains both treatment and control groups. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Panel A: Extensive Margin

Dependent Var	All DLQ	Credit Card	Auto	Mortgage	All DLQ	Credit Card	Auto	Mortgage
	Accounts (Ex. Stud)	DLQ Accounts	DLQ Accounts	$\begin{array}{c} \mathrm{DLQ} \\ \mathrm{Accounts} \end{array}$	Accounts (Ex. Stud)	DLQ Accounts	DLQ Accounts	DLQ Accounts
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$DebtRelief \times Post$	-0.12***	-0.11***	-0.001	-0.01**	-0.12***	-0.11***	0.001	-0.01**
	(0.021)	(0.020)	(0.004)	(0.003)	(0.021)	(0.019)	(0.004)	(0.004)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	No	No	No	No
County \times Month FE	No	No	No	No	Yes	Yes	Yes	Yes
Observations	6,010,381	6,010,381	6,010,381	6,010,381	6,010,381	6,010,381	6,010,381	6,010,381
\mathbb{R}^2	0.73	0.72	0.69	0.76	0.78	0.77	0.74	0.8
Panel B: Intensive Me	argin							
Dependent Var	All DLQ	Credit Card	Auto	Mortgage	All DLQ	Credit Card	Auto	Mortgage
	Amount	DLQ	DLQ	DLQ	Amount	DLQ	DLQ	DLQ
	(Ex. Stud)	Amount	Amount	Amount	(Ex. Stud)	Amount	Amount	Amount
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$DebtRelief \times Post$	-408.69***	-62.87***	-2.64	-410.57***	-214.91***	-63.36***	7.37	-210.42***
•	(56.99)	(11.39)	(15.36)	(45.85)	(59.56)	(11.76)	(15.61)	(58.39)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	No	No	No	No
County \times Month FE	No	No	No	No	Yes	Yes	Yes	Yes
Observations	6,010,381	6,010,381	6,010,381	6,010,381	6,010,381	6,010,381	6,010,381	6,010,381
\mathbb{R}^2	0.62	0.63	0.61	0.47	0.69	0.71	0.67	0.55

Table 7: Student Debt Relief and Mobility

This table reports results from difference-in-differences regressions of consumer mobility outcomes based on borrower-month panel data. The sample is split into individuals who default only on student loans and those who default on multiple loans. The dependent variable are indicators of moving: mobility based on moving to a different state in Panel A; job mobility based on moving to a different industry (NAICS two-digit) in Panel B; job mobility based on moving to a higher-paying job in different industry (NAICS two-digit) in Panel D. DebtRelief is defined as 1 for the delinquent student loans who received debt relief and 0 otherwise. Post is defined as 1 for 36 months after the debt relief and 0 for 36 months before the debt relief. On the right hand side, we control for individual fixed effects in all columns. Additionally, we control for credit report month fixed effects in Columns (1)—(3) and county \times month fixed effects in Columns (2)—(4). Standard errors are clustered at ZIP Code level. The regression is based on borrower \times month panel data that contains both treatment and control groups. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Panel A: Mobility				
Dependent Var		Mobility (State)	
	(1)	(2)	(3)	(4)
$DebtRelief \times Post$	0.004*	0.004**	0.001	0.001
	(0.002)	(0.002)	(0.001)	(0.001)
Sub-Sample	Defaulted on	ly on Student Loans	Defaulted or	n Multiple Loans
Individual FE	Yes	Yes	Yes	Yes
Month FE	Yes	No	Yes	No
County x Month FE	No	Yes	No	Yes
Observations	2,372,038	2,372,038	3,565,125	3,565,125
\mathbb{R}^2	0.52	0.72	0.47	0.66
Panel B: Job Mobili	ty			
Dependent Var		Job Mob	oility	
	(1)	(2)	(3)	(4)
$DebtRelief \times Post$	0.01***	0.008**	0.001	0.002
·	(0.003)	(0.003)	(0.002)	(0.002)
Sub-Sample	Defaulted on	ly on Student Loans	Defaulted or	n Multiple Loans
Individual FE	Yes	Yes	Yes	Yes
Month FE	Yes	No	Yes	No
County x Month FE	No	Yes	No	Yes
Observations	356,970	356,970	594,502	594,502
\mathbb{R}^2	0.14	0.53	0.13	0.47

Panel C: Moving to New Industry

Dependent Var		Moving to Nev	v Industry	
	(1)	(2)	(3)	(4)
$DebtRelief \times Post$	0.01***	0.007**	-0.001	0.001
·	(0.003)	(0.003)	(0.002)	(0.002)
Sub-Sample	Defaulted of	only on Student Loans	Defaulted of	on Multiple Loans
Individual FE	Yes	Yes	Yes	Yes
Month FE	Yes	No	Yes	No
County x Month FE	No	Yes	No	Yes
Observations	356,893	356,893	594,411	594,411
\mathbb{R}^2	0.13	0.52	0.12	0.47
Panel D: Moving to	Higher Payir	ng Industry		
Dependent Var		Moving to Higher F	Paying Industr	У
	(1)	(2)	(3)	(4)
$DebtRelief \times Post$	0.02***	0.017**	-0.001	-0.004
·	(0.006)	(0.008)	(0.004)	(0.005)
Sub-Sample	Defaulted of	only on Student Loans	Defaulted of	on Multiple Loans
Individual FE	Yes	Yes	Yes	Yes
Month FE	Yes	No	Yes	No
County x Month FE	No	Yes	No	Yes
Observations	85,757	85,757	147,130	147,130
\mathbb{R}^2	0.23	0.81	0.23	0.76

Table 8: Student Debt Relief and Income

This table reports results from difference-in-differences regressions of consumer income based on borrower-month panel data. The sample is split into individuals who default only on student loans and those who default on multiple loans. The dependent variable is the total employment income. DebtRelief is defined as 1 for the delinquent student loans who received debt relief and 0 otherwise. Post is defined as 1 for 36 months after the debt relief and 0 for 36 months before the debt relief. On the right hand side, we control for individual fixed effects in all columns. Additionally, we control for credit report month fixed effects in Columns (1)—(3) and county \times month fixed effects in Columns (2)—(4). Standard errors are clustered at ZIP Code level. The regression is based on borrower \times month panel data that contains both treatment and control groups. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Dependent Var	Income (\$)				
	(1)	(2)	(3)	(4)	
$DebtRelief \times Post$	90.62** (43.44)	111.82*** (44.75)	34.93 (33.88)	54.18 (42.73)	
Sub-Sample		only on Student Loans		on Multiple Loans	
Individual FE	Yes	Yes	Yes	Yes	
Month FE	Yes	No	Yes	No	
County x Month FE	No	Yes	No	Yes	
Observations	158,492	158,492	300,459	300,459	
\mathbb{R}^2	0.15	0.43	0.12	0.32	

Table 9: Student Debt Relief and New Car Purchase

This table reports results from difference-in-differences regressions of new loans based on borrower-month panel data. The sample is split into individuals who default only on student loans and those who default on multiple loans. The dependent variable is new car indicator. DebtRelief is defined as 1 for the delinquent student loans who received debt relief and 0 otherwise. Post is defined as 1 for 36 months after the debt relief and 0 for 36 months before the debt relief. On the right hand side, we control for individual fixed effects in all columns of both panels. Additionally, we control for credit report month fixed effects in Columns (1)—(3) and county \times month fixed effects in Columns (2)—(4). Standard errors are clustered at ZIP Code level. The regression is based on borrower \times month panel data that contains both treatment and control groups. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Dependent Var	New Car Indicator					
	(1)	(2)	(3)	(4)		
$DebtRelief \times Post$	0.004** (0.002)	0.003* (0.002)	0.0002 (0.001)	0.001 (0.001)		
Sub-Sample	Defaulted on	ly on Student Loans	Defaulted on Multiple Loans			
Individual FE	Yes	Yes	Yes	Yes		
Month FE	Yes	No	Yes	No		
County x Month FE	No	Yes	No	Yes		
Observations	2,372,038	2,372,038	3,565,125	3,565,125		
\mathbb{R}^2	0.15	0.43	0.12	0.32		

Table 10: Student Debt Relief and New Student Loan

This table reports results from difference-in-differences regressions of new loans based on borrower-month panel data. The sample is split into individuals who default only on student loans and those who default on multiple loans. The dependent variable is new student loan indicator. DebtRelief is defined as 1 for the delinquent student loans who received debt relief and 0 otherwise. Post is defined as 1 for 36 months after the debt relief and 0 for 36 months before the debt relief. On the right hand side, we control for individual fixed effects in all columns of both panels. Additionally, we control for credit report month fixed effects in Columns (1)—(3) and county \times month fixed effects in Columns (2)—(4). Standard errors are clustered at ZIP Code level. The regression is based on borrower \times month panel data that contains both treatment and control groups. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Dependent Var	New Student Loan Opening				
	(1)	(2)	(3)	(4)	
$DebtRelief \times Post$	0.01*** (0.002)	0.01*** (0.002)	0.002 (0.001)	0.002* (0.001)	
Sub-Sample	Defaulted on	ly on Student Loans	Defaulted on Multiple Loans		
Individual FE	Yes	Yes	Yes	Yes	
Month FE	Yes	No	Yes	No	
County x Month FE	No	Yes	No	Yes	
Observations R ²	2,372,038 0.13	2,372,038 0.37	3,565,125 0.11	3,565,125 0.29	

Table 11: Heterogeneity Analysis of Borrowing Behavior

This table reports results from difference-in-differences regressions of consumer debt strategies based on borrower-month panel data. Compared to previous tables, we include the triple interactions to account for the heterogeneity in borrower characteristics. In both panels, the dependent variables are total debt balance in Column (1); mortgage balance in Column (2); revolving utilization in Column (3); indicator of any delinquent account in Column (4); indicator of moving to different ZIP Code in Column (5). In Panel A, we include the triple interaction $DebtRelief \times AboveMedianAge \times Post$. In Panel B, we include the triple interaction $DebtRelief \times AboveMedianTotalDebt \times Post$. DebtRelief is defined as 1 for the delinquent student loans who received debt relief and 0 otherwise. Post is defined as 1 for 36 months after the debt relief and 0 for 36 months before the debt relief. On the right hand side, we control for individual fixed effects and county \times month in all columns. Standard errors are clustered at ZIP Code level. The regression is based on borrower \times month panel data that contains both treatment and control groups. Asterisks denote significance levels (***=1%, **=5%, *=10%).

$Panel\ A:$	Hetero	geneity	by	Age
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Dependent Var	Total Debt (Ex, Stud)	Mortgage Balance	Credit Card Utilization	DLQ Indicator (Ex. Stud)	Mobility
	(1)	(2)	(3)	(4)	(5)
$DebtRelief \times Above \times Post$	-5,328.98***	-766.68**	-0.001	-0.13***	0.002*
	(1424.53)	(310.57)	(0.01)	(0.04)	(0.001)
$DebtRelief \times Post$	-1,315.82*	-152.26	-0.02***	0.004	0.001
	(765.22)	(156.31)	(0.007)	(0.026)	(0.001)
$Above \times Post$	-3,292.94***	-970.66***	-0.004**	-0.18***	-0.003***
	(368.38)	(81.19)	(0.00)	(0.01)	(0.000)
Individual FE	Yes	Yes	Yes	Yes	Yes
County \times Month FE	Yes	Yes	Yes	Yes	Yes
Observations	6,010,381	6,010,381	6,010,381	6,010,381	6,010,381
\mathbb{R}^2	0.2	0.83	0.7	0.77	0.53

Panel B: Heterogeneity by Total Debt (Excluding Student Loans)

Dependent Var	Total Debt (Ex, Stud)	Mortgage Balance	Credit Card Utilization	DLQ Indicator (Ex. Stud)	Mobility
	(1)	(2)	(3)	(4)	(5)
$\overline{DebtRelief \times Above \times Post}$	-7,718.34***	-1,401.53***	-0.04***	-0.08**	0.001
	(1263.41)	(294.33)	(0.01)	(0.04)	(0.002)
$DebtRelief \times Post$	262.52	207.62	0.03***	0.009	0.001
	(400.12)	(147.90)	(0.01)	(0.02)	(0.001)
$Above \times Post$	-3,070.22***	-758.35***	-0.07***	-0.28***	-0.001***
	(315.63)	(74.67)	(0.00)	(0.01)	(0.000)
Individual FE	Yes	Yes	Yes	Yes	Yes
County \times Month FE	Yes	Yes	Yes	Yes	Yes
Observations	6,010,381	6,010,381	6,010,381	6,010,381	6,010,381
\mathbb{R}^2	0.2	0.83	0.7	0.77	0.53